Why Beauty Matters*

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Abstract

We decompose the beauty premium in an experimental labor market where ‘employers’ pay wages to ‘workers’ who perform a maze-solving task. This task requires a true skill which we show to be unaffected by physical attractiveness. We find a sizable beauty premium but no evidence for direct taste-based discrimination. Instead, we can identify three indirect transmission channels. (1) Physically-attractive workers are more confident which helps them to obtain higher wages. This effect explains about 20 percent of the beauty premium. (2) Physically-attractive workers are (wrongly) considered more able by employers. This *direct stereotype* effect is responsible for about 30 percent of the premium. (3) Physically-attractive workers have certain skills (such as communication and social skills) which raise their wages when they interact verbally with employers. This *indirect stereotype* effect contributes to the remaining 50 percent of the beauty premium.

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1 Introduction

In their seminal work, Hamermesh and Biddle (1994) found that physically attractive workers derive sizable rents from their looks. Workers of above average beauty earn about 10 to 15 percent more than workers of below average beauty. The size of this *beauty premium* is economically significant and comparable to the race and gender gaps in the US labor market.

How does physical attractiveness translate into such a large wage differential? An obvious explanation is that physically attractive workers are simply more productive when interacting with customers and coworkers. There is some empirical support for this hypothesis in certain occupations: Biddle and Hamermesh (1998) conclude that physical attractiveness raises lawyers' wages because clients prefer attractive lawyers and Pfann, Bosman, Biddle, and Hamermesh (2000) show that physically attractive executives in advertising agencies benefit from physical attractiveness due to better interaction with both customers and coworkers. However, productivity-related compensation does not seem to contribute significantly to the overall beauty premium which has been measured across occupations. Hamermesh and Biddle (1994) find that accounting for the intensity of interpersonal interaction with customers and co-workers has almost no effect on the cross-sectional beauty premium. Therefore, it is quite plausible that the higher wages of the physically attractive versus their less beautiful but equally qualified compatriots arise during the wage determination game between worker and employer where the physically attractive manage to extract greater rents.

We study how such rents are formed during a wage determination process in an experimental labor market. Our subjects, drawn from a pool of undergraduate and graduate students from Tucuman, Argentina are divided into workers who are "hired" to perform a skilled task of solving computer mazes, and employers who set their wages. All workers become employed but can receive different compensation. Workers solve one practice maze at the start of the experiment. Compensation incentives are set to induce them to truthfully reveal how many mazes they believe they will be able to solve during a 15 minute "work period". Before the "work period" begins, workers interact with employers who determine their wages. Similarly, the incentives for employers encourage them to set wages that correspond to their impressions of workers' maze-solving skills. Finally, workers are paid a piece rate for each solved maze. Our beauty measure is constructed from ratings by a panel of independent evaluators. Hatfield and Sprecher (1986) document that physical attractiveness ratings of facial photographs are remarkably stable across genders and cultures.

The advantage of our experimental methodology is that we can observe the interaction between employer and worker in our artificial labor market. In survey data, such information is typically not available and the entire wage negotiation process has to be treated instead as a black box.

We find a sizable beauty premium in our experiment which is comparable to the beauty premium found in the real-world data. However, we also show that physically attractive workers are in fact no better in solving mazes than less attractive ones. We build a simple model to decompose this beauty premium. We assume that both employer and employee enter the wage negotiation with some prior beliefs about the worker's ability. We call physical features of the worker which bias the employer's prior perception of his ability *stereotypes*. We call the worker's prior belief of his ability his *confidence*. After interacting with the employee, the employer makes a wage offer which equals her best posterior belief of the worker's ability. If an employer has a taste for rewarding a beautiful employee she can shade her wage offer and set a wage which is higher than her belief of the worker's ability.

The model allows us to identify four different channels through which the beauty premium can arise. First, worker's beauty can raise the employer's perception of his ability through the *stereotype channel*. We further distinguish between the direct stereotype channel which operates through simple visual interaction and the indirect stereotype channel which requires verbal communication. We can attribute about 80 percent of the beauty premium to these two channels - 30 percent due to direct stereotype effects and 50 percent due to indirect effects. Second, we show that beauty raises worker's confidence which in return raises her wage. This effect explains about 20 percent of the beauty premium. Third, we test for the presence of a *persuasion channel* in which beauty increases the weight the employer attaches to the worker's confidence versus his own prior. We find no evidence for this channel. Finally, it is possible that neither employers' nor workers' beliefs are affected by physical attractiveness but that employers simply have a taste for employing beautiful workers. We also find no evidence for this *Becker-type discrimination hypothesis*.

The decomposition is possible because we can control the mode of interaction in our experiments. Each worker interacts with five different employers. All employers can see the "resume" of the employee. In addition to the basic information regarding education, age, previous employment and hobbies, the "resume" also includes the time it took the employee to solve the practice maze. The first employer evaluates only the "resume" information. The second employer additionally sees the facial photograph of the worker. The third employer conducts a telephone "interview" but does not see the photograph. The fourth employer both talks to the worker on the telephone and sees the photograph. Finally, the fifth employer is presented with the richest set of stimuli - a face-to-face "interview" with the worker.

Our stereotype hypothesis builds on a large body of work in social psychology on the *physical attractiveness stereotype*. Often summarized under the catchphrase "beauty is good" this research has demonstrated that beauty is perceived to be correlated with intelligence, social skills, health and sexual warmth to name just a few of the positive attributes bestowed upon physically attractive people. Interestingly, this line of research has found no actual correlation between physical attractiveness and cognitive ability which is consistent with the findings of our experiment where physical attractiveness did not affect maze-solving ability.

Our confidence hypothesis reflects the growing consensus that (a) non-cognitive skills contribute crucially to labor market success; and (b) that physical attributes such as beauty and height can affect the acquisition of non-cognitive skills. Evidence from early childhood intervention programs such as the Perry preschool program demonstrates that these programs can raise lifetime earnings by improving students' social skills and motivation rather than through gains in cognitive abilities which are short-lived and dissipate over time (see Heckman (2000)). Persico, Postlewaite, and Silverman (2001) analyze the well-known height premium which is comparable in magnitude to those associated with beauty, gender and race. They find that only height at 16 rather than adult height matters: this suggests that height promotes the acquisition of non-cognitive social skills such as confidence and the ability to interact socially with others, which then in return increases wages. The fact that this indirect channel rather than the direct effect of adult height has an impact on wages raises the question whether physical attractiveness also increases wages by promoting the acquisition of non-cognitive skills. Certainly, there is overwhelming anecdotal evidence that people do recognize the income-enhancing effects of confidence: almost every self-help book emphasizes the need for "positive thinking" and for self-esteem as one of the keys to success. Parents are continuously reminded to use positive reinforcement in interactions with their children in order to build self-esteem and instill confidence in them. Team sports and group activities are encouraged not just because students benefit from physical activity but because they can enhance self-esteem.

The balance of the paper is organized as follows. In section 2 we discuss related literature in economics and social psychology. Section 3 presents a simple theoretical framework for decomposing the beauty premium. Section 4 describes the design of the experiment and our empirical strategy. Section 5 discusses our experimental data. In section 6 we establish that there is a beauty premium and test for the various channels through which beauty raises workers' wages in our experiment. Section 7 concludes.

2 Literature Review

Our work is related to three bodies of literature on the role of physical attractiveness in the labor market: a small but growing literature in labor economics starting with the seminal paper by Hamermesh and Biddle (1994), a large and well-established literature on physical attractiveness in the fields of social psychology and human resource management, and a small number of experimental papers which look at the link between physical attractiveness and economic outcomes.

When exploring the sources of the beauty premium, the empirical labor literature has focused on the question whether physical attractiveness makes workers more productive in occupations where there is a great deal of interpersonal interaction with customers or co-workers. There are two basic explanations for such productivity differences: pure discrimination of customers and co-workers against the non-beautiful and a greater ability by the beautiful to acquire social skills which in return give rents. These skills include interpersonal skills such as persuasion which might be productivity enhancing in dealings with customers. Beauty might also increase the ability to cooperate with coworkers which are shared with the employer.[1] Pfann, Bosman, Biddle, and Hamermesh (2000) show that the social capital hypothesis is the most likely explanation for the observed correlation between executive beauty and firm revenue growth in their analysis of the Dutch advertising industry.

Hamermesh and Biddle (1994) attribute most of the beauty premium to employer discrimination[2]. However, this assertion cannot be adequately tested without knowing details about the nature of interaction between the worker and the

[1] Mulford, Orbell, Shatto, and Stockard (1998) found such a strategic effect of beauty in their study when they observed that subjects in a Prisoner's Dilemma expected beautiful opponents to cooperate more often and good-looking subjects were also more likely to cooperate themselves even after controlling for their perceptions of the opponent's move. Note that sometimes physically attractive workers can become more productive at the expense of less attractive workers (if beauty is used to obtain favors from those workers). These zero sum games should *not* affect wages of beautiful workers.

[2] In certain occupations, such as among lawyers beauty can help with customer relationships (see Biddle and Hamermesh (1998)).

employer: as explained in the introduction the beauty premium might also be generated through an indirect channel such as employer stereotypes and worker confidence. Moreover, the fact that none of the height premium is attributable to direct discrimination against short people should make us at least suspicious of Becker-type discrimination as a full explanation (Persico, Postlewaite, and Silverman 2001).

Another reason for the scarcity of empirical studies on stereotypes and confidence effects in labor economics might be the assumption of standard models that agents have unbiased beliefs about their own ability and the ability of others. However, at least for workers it is not obvious that there exists a Bayesian notion of belief in a job interview context. Most jobs are only incompletely described and the distribution of a worker's true future performance in some specific job is at least somewhat unknown. This gives the worker some degree of discretion in choosing her belief about her own ability. In our experiment, for example, "workers" systematically underestimate their ability to solve mazes by a factor of almost 30 percent.

In contrast, the social and experimental psychology literatures have for a long time looked at non-Becker type effects of beauty. One of the main questions of this literature is how beautiful people are perceived by others? The main experimental findings are that more beautiful people are viewed superior along several dimensions: personality traits (sociability, dominance, sexual warmth, modesty, character), mental health, intelligence and academic ability, and social skills (Feingold 1992, Eagly, Ashmore, Makhijani, and Longo 2001). The correlation is intermediate for personality measures, weak for intelligence and strongest for social skills. This observation is often referred to as the physical attractiveness or *beauty-is-good* stereotype.

The social psychology literature also analyzes to what extent there is a *kernel of truth* to this stereotype. There is substantial evidence that attractive people are treated better by others throughout their life-cycle.[3] Moreover facial attractiveness rating does not appear to change much both during childhood (see Adams (1977a) and throughout adulthood (see Adams (1977b)). Physically attractive people might therefore develop different expectations and skills (particularly social skills) from less attractive people. The attractiveness stereotype can thus become a self-fulfilling prophecy giving rise to confidence and persuasion ability effects in our setup. In his large meta-analysis comprising between 900 and 3000 subjects Feingold (1992) found that there is only a trivial correlation between physical attractiveness and most measures of personality traits and cognitive ability.[4] However, he also showed that there is intermediate correlation between beauty and absence of social anxiety, and significant correlation between beauty and popularity (about .29) and, in particular, social skills (about .25).[5]

Confidence is therefore a potential transmitter of beauty effects. The social psychology literature has employed various measures to capture confidence, self-esteem and 'self-efficacy' which are designed to assess optimistic self-beliefs to

[3]Teachers expect better looking kids to do better in school and they devote more attention to the children who they think have better potential (see Hatfield and Sprecher (1986)). Attractive people are also more likely to receive more favors from others

[4]Similarly, Jackson, Hunter, and Hodge (1995) found that attractiveness was related to intellectual competence for children but not for adults.

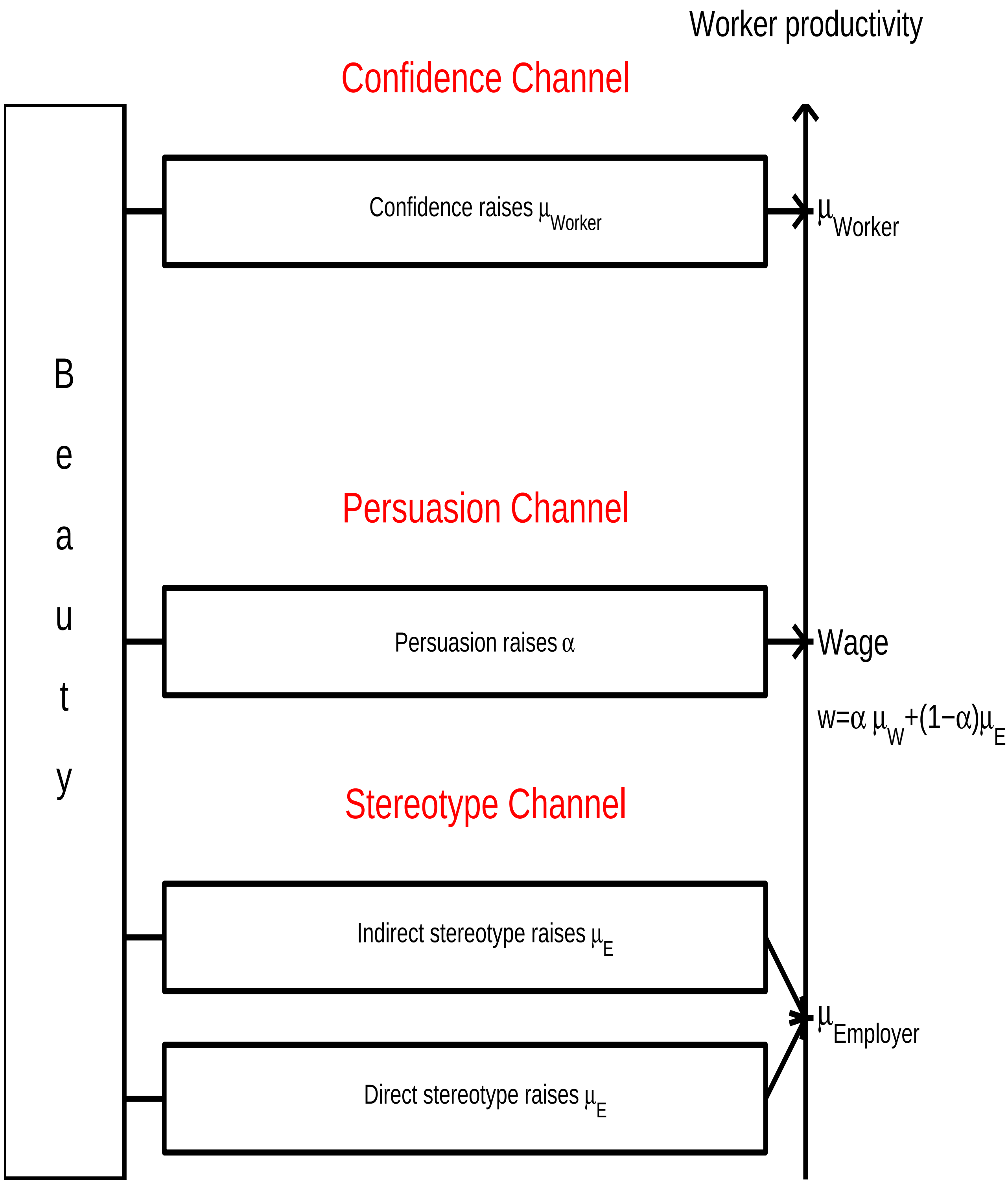
[5]In one of the studies included in the meta-analysis Goldman and Lewis (1977) reported that subjects found more attractive people more persuasive in telephone conversations even if they had not seen the faces of their counterparts. However, the strength of the correlation between beauty and characteristics of subjects vary considerably between studies. Bull and Stevens (1981) could not replicate the results by Goldman and Lewis (1977). In another study, Chaiken (1979) found that attractive communicator-subjects were more successful in delivering a persuasive message.

cope with a variety of difficult demands in life (see Cassidy and Long (1996), Lorr and Wunderlich (1986) and Mittag and Schwarzer (1993)). The measures are by construction broad and lack an obvious metric. An advantage of a task-specific measure of confidence such as ours is that it can overcome both of these problems and thereby reduce measurement errors and make the estimation results easier to interpret.

The use of an experimental framework to decompose the beauty premium is novel to the best of our knowledge. Notable exceptions are the contributions by Solnick and Schweitzer (1999) who look at the influence of physical attractiveness on ultimatum game decisions, and Mulford, Orbell, Shatto, and Stockard (1998) as well as Kahn, Hottes, and Davis (1971) on the Prisoner's Dilemma. However, we view neither the Prisoner's Dilemma nor the ultimatum game as adequate descriptions of wage setting in labor markets because there is no notion of skill in these games.

3 Theoretical Framework for Decomposing the Beauty Premium

We use a simple model of wage determination to analyze our data. The central part of the model describes the belief formation of the employer about the worker's ability. The employer has some prior belief μ_E about the worker's ability and the worker has his own belief μ_W captured by his confidence. The employer forms a posterior belief w which represents her best guess about the worker's ability. If



Worker productivity
Confidence Channel
Confidence raises μWorker
μWorker
B e a u t y
Persuasion Channel
Persuasion raises α
Wage
w=α μW+(1−α)μE
Stereotype Channel
Indirect stereotype raises μE
μEmployer
Direct stereotype raises μE

there is no direct taste-based discrimination the employer should set the wage to be his posterior belief w. Otherwise, the final wage will be $w + D(B)$ where the discrimination component $D(B)$ is an increasing function of B.

We describe the posterior belief formation process in greater detail below. The following thought experiment helps to fix ideas. Imagine the following stylized job interview which consists of two stages: "first impression" and "job discussion". In the first few moments of the interview, worker and employer engage in small talk unrelated to job requirements or candidate's qualifications. The employer is going to form her "first impression" of the worker. At this point, what we call the *stereotype channel* is going to influence employer's beliefs about worker's ability. The *direct stereotype channel* works through visual interaction. The employer is going to associate a higher skill level with a more physically attractive candidate. This is a consequence of beauty-is-good stereotype from the psychology literature that we discussed earlier. In conjunction with pure visual interaction, the employer will have a chance to engage in oral communication and observe social skills of the candidate. During this verbal interaction *indirect stereotype channel* can have an impact on employer's beliefs. Kernel-of-truth hypothesis from the psychology literature suggests that beauty-is-good stereotype might in fact be justified because good looking people have developed better (social) skills through preferential treatment or genetics. If the skills that are correlated with beauty can manifest themselves in verbal interaction such as better rhetorical and overall communication skills, then a more physically attractive person will successfully increase employer's beliefs about his ability. Both direct and indirect stereotype channels will have an impact on employer's belief about worker's ability, $\mu_{Employer}$.

After employer forms her prior belief, the next stage of the interview takes place in which job requirements are discussed and the worker has a chance to persuade the employer about his ability. The worker comes into the interview room with his own prior about his ability. He forms this belief based on his confidence about performing the task. If beauty enhances worker's confidence, then we can expect more good-looking candidates to form more optimistic estimates based on their initial trial time. Physical attractiveness then influences worker's belief about his ability, μ_{Worker}, through the *confidence channel*. To summarize, before engaging in conversation about the job itself, both employer and employee form their respective estimates of employee's ability. During the second stage of the interview, the wage $w = \alpha\mu_{Worker} + (1-\alpha)\mu_{Employer}$ gets determined. The coefficient α is influenced through the *persuasion channel*. A more physically attractive candidate might be more successful at convincing the employer that his own estimate of his ability is correct.

4 Experimental Design and Procedure

In our experiment there are workers and employers who interact in an artificial labor market. Workers have the task to solve as many computer mazes as possible within a 15 minute period. The mazes can be found at the Yahoo website.[6] These mazes were first used in experimental research by Gneezy, Niederle, and Rustichini (2002). It is important for us that maze solving requires a certain type of cognitive skill and the ability to concentrate for an extended period of time. It does not require any non-cognitive skill such that we can abstract away from productivity-

[6]http://games.yahoo.com/games/kidsmz.html

enhancing explanations of the beauty premium.

We allow subjects to perform a practice maze at the easiest difficulty level (there are five levels of difficulty from the easiest, level 1, to the hardest, level 5). Each worker is then interviewed by employers who set his wages based on their estimates of his productivity. Finally, workers perform in the 15 minute trial and are paid a piece rate.

Maze-solving exhibits various dimensions of uncertainty. First, there is considerable variation in ability: in our sample the mean number of solved mazes is 9.53 with a standard variation of 3.86. Second, for almost all workers and employers the task is unfamiliar. Third, there is a significant amount of learning going on during the 15 minute trial: the average level 1 practice maze takes 127 seconds to solve while the average level 2 maze is solved in only 94 seconds. Fourth, the practice maze is only somewhat informative about a worker's ability since there is significant variation in the difficulty of mazes even within the same level and because the 15 minute trial has harder mazes (we do not show level 2 mazes to the workers before the trial). Fifth, there is no obvious focal point (other than simply extrapolating from the performance in the practice maze).

Taken together, these different layers of uncertainty make it hard for both workers and employers to predict the productivity. For this reason we expect confidence, persuasive skills and stereotypes to play a large role in determining wages. We believe that such an environment is representative of real labor market conditions where it be might easy to establish the formal qualification of a worker for a specific job but where there remains considerable uncertainty about the match quality.

4.1 Description of Experimental Design

We now describe the experimental design in detail. In our experiment ten subjects are invited to the lab - five of them are assigned the role of the 'worker' and the other five are 'employers' numbered 1 through 5. The group of workers and each employer are moved to separate rooms where the instructions of the game are read to them. The instructions for workers and employers in Spanish and English are provided in appendix A and B.

Workers fill out a resume form which asks for their age, sex, university, matriculation year, previous job experience and extracurricular activities. This basic resume information can be later viewed by all five employers on a standardized form. We also collect the same information from employers. Employers start with an initial account of 4000 credits. Workers have no credits at the beginning of the game.

Workers are explained that they have to solve as many randomly generated computer mazes as possible during a 15 minute period at the end of the experiment. They are told that there are various levels of difficulty and that mazes can vary in their difficulty even within a single level. They are also informed that players frequently improve their maze-solving skill substantially through practice.

Each worker then goes on to solve one practice maze at the easiest level. His time is top-coded after 5 minutes and becomes part of his resume - thus every employer can see the practice time of every worker she interviews. None of this information is shared amongst workers who are instructed not to talk to each other.

After the practice maze each worker j is asked to reveal his best estimate C_j of his performance in the 15 minutes trial at the end of experiment. This information is kept secret from all other players. However, for any discrepancy between the estimated number of mazes and the actually solved number of mazes 40 credits are subtracted from the final winnings for each maze. The workers are explained in the instructions that the statistically optimal answer to this question is to report the median of the perceived productivity distribution.[7] We equate the estimated number of mazes with the *confidence* of the worker.

Each worker then interviews with *all* of the employers. The order in which players interview with employers is randomized to avoid order effects. All employers see the same resume of each worker (including practice time) but differ in the mode of interaction with the worker:[8]

0: Employer 0 only sees the resume of the worker.

P: Employer P sees the resume and a frontal facial passport-like photograph of the worker.

T: Employer T sees the resume and conducts a free-form telephone interview with the worker of up to 5 minutes in length.

PT: Employer PT sees the resume, the photograph and also conducts a telephone conversation of up to 5 minutes in length.

[7]Specifically, subjects are told that at the median they are equally likely to be above their estimate as they are to fall below the estimate. We did not use a quadratic punishment scheme to reveal the expected mean of the perceived distribution because we wanted to limit the size of the maximum penalty and also keep it as transparent as possible.

[8]Note that we distinguish between treatment PT (picture + verbal interaction) and true face-to-face communication. Numerous studies have shown that non-verbal cues are powerful predictors of interpersonal evaluations (see Straus, Miles, and Levesque (2001) for an overview). Non-verbal signals help to form initial evaluations and cues such as eye contact amplify these first impressions (Hemsley and Doob 1978).

FTF: Employer FTF sees the resume, the photograph and also conducts a face-to-face free form interview with the worker of up to 5 minutes in length.

Employers can take notes during their interviews with workers. After an employer i (where $i \in O, P, T, PT, FTF$ has interviewed all five workers $j = 1..5$ she has to determine a 'wage' w_{ij} for all five interviewed workers simultaneously. Payoffs to employers are structured in such a way that the wage setting game resembles a competitive labor market where workers are paid according to their expected productivity. In our experiment the employer does not pay wages directly - instead they are paid out by the experimenter. With 80 percent probability a worker j receives 100 credits times employer's wage and with 20 percent probability the worker receives the average wage $\overline{w}$ set by all employers in this experimental session times 100 credits. The actual wage $\hat{W}_{ij}$ of worker j from employer i is therefore:

$$\hat{W}_{ij} = \begin{cases} 100 \times w_{ij} & \text{with probability } 0.8 \\ 100 \times \overline{w} & \text{with probability } 0.2 \end{cases} \tag{1}$$

The employer in return is penalized by 40 credits per maze for any discrepancy between the wage w_{ij} and worker j's productivity A_j (measured by total number of mazes solved during the subsequent 15 minute trial). The total winnings Π_i of employer i are calculated as follows:

$$\Pi_i = 4000 - \sum_{j=1}^{5} 40 \times |w_{ij} - A_j| \tag{2}$$

The optimal strategy of the employer is to set the wage of the worker always equal to her median estimate of the ability of the worker regardless of whether he actually sets the wage. This wage setting procedure is carefully explained to employer subjects.

Neither the worker nor the employer know during the interview whether the employer will in fact determine the wage of the worker: they only know that the employer will do so with 80 percent probability. Only after the interviews when inputting the wages for each worker the employer finds out which worker will receive the wage and who will receive a wage average. This randomization tests for pure discrimination: if the employer has a taste for physically attractive subjects we expect the employer to set higher wages if the worker will also receive that wage.[9]

After all the interviews are over, workers go through the 15 minute work period solving mazes of difficulty level 2. They are paid a piece rate of 100 credits for each solved maze. One implication of our experimental design is that the effective piece rate of workers is 140 credits for each maze as long as they stay below their estimate and only 60 credits for each maze thereafter. Unfortunately, there is no way to elicit truthful revelation of workers' beliefs before they start the trial without distorting incentives during the trial. However, we chose a sufficiently large exchange rate from credits to money to ensure that even 60 credits represent a salient reward. The total compensation Π_j of the worker can be calculated as follows:

$$\Pi_j = 100 \times A_j - 40 \times |C_j - A_j| + \sum_{i=1}^{5} 100 \times W_{ij} \tag{3}$$

[9]It is important in our design that the employer does not know at the interview phase whether the worker will actually receive the wage she sets. Otherwise, the employer could inform the worker about this fact and the worker would have no incentive to convince the employer of his ability. It would be akin to a job interview where the worker knows in advance that he will not get the job.

4.2 Measurement of Confidence

We use the worker's estimate of his productivity as our measure of worker confidence. This implies that a subject with high maze solving ability will on average have greater confidence if she is at least somewhat aware of her ability. The colloquial use of confidence is quite imprecise: at least some of our colleagues preferred an alternative measure of confidence such as the difference between the estimated and the actual number of rounds in order to distinguish between 'justified' confidence and 'excess' confidence.

We decided to use the simple estimated productivity as our confidence measure because it gives us the greatest flexibility. We find it hard to distinguish between 'justified' and 'excess' confidence: a subject who is convinced she can solve 15 mazes during the 15 minutes trial cannot make this decomposition if, for example, his true ability is only 10 and his excess confidence is 5. Presumably, if he had known that his true ability is only 10 he would have said 10 instead of 15.

In any case, there is no formal difference when we use the estimated number of rounds or the deviation of the estimate from the true number. In all our regressions we control for actual productivity interacted with modes of communication dummies. Therefore the estimated coefficients on both confidence measures would have been identical.

4.3 Experimental Procedure

We conducted 33 experimental sessions at Universidad Nacional de Tucuman (UNT), Tucuman, Argentina from August 2002 to March 2003. Subjects were recruited at three different university campuses in the city of Tucuman - Universidad Nacional de Tucuman, Universidad del Norte Santo Tomas de Aquino (UNSTA), Univesidad Tecnologica Nacional (UTN) with approximately 87% of subjects coming from the (UNT) campus. Both UNT and UTN are public universities with tuition of 20 pesos per year. UNSTA is a private university that typically draws students from upper middle class families since tuition ranges from 1300 to 2700 pesos per year depending on the major. UTN is an institute of technology with engineering and computer science majors only. Upon arrival to the UNT experimental lab, subjects were randomly assigned to be either an employer or employee. We took special precautions to make sure that subjects did not know each other prior to the experiment and did not communicate with each other before the start of the experiment.

Each subject received a participation fee of 12 Peso plus his winnings from the experiment. The average hourly wage at the time in Tucuman was about 6 Peso. For calculating the earnings we used an exchange rate of 100 credits $\cong$ 0.25 Peso. The game lasted on average one to one and a half hours and the average winnings were 14.34 Peso. Subjects were paid in cash at the end of the experiment.

The five workers were sitting in the main computer lab and the employers were allocated to different rooms. The entire game including instructions and exit questions was played on the computer using a web-based Spanish interface. The instructions were also read aloud and included practice questions with answers to check whether subjects had understood the instructions.[10]

We were careful to present the pictures of workers in a uniform manner. The pictures were taken using a digital camera and immediately converted to uniform

[10] The practice questions asked subjects to calculate winnings in various scenarios.

size showing a frontal facial image of the worker. There are two reasons for restricting ourselves to facial photographs only. First of all, we did not want to reveal to employers how workers dressed (except in treatment FTF with face-to-face communication where it was unavoidable). Hamermesh, Xin, and Junsen (1999) have shown that workers invest considerable resources in improving their appearances, for example, through expensive clothing. Second, while there is broad cross-cultural agreement on the ranking of facial photographs, the same is not true for body types. In some developing countries, for example, a high body mass index is considered to be a desirable sign of affluence (Hatfield and Sprecher 1986).

We also tried to ensure that workers in the main lab did not communicate with each other during the experiment so that they would not be influenced by the performance of other players when making estimates.

5 Data

5.1 Summary Statistics

Subject pool characteristics are drawn from information subjects provided when they registered for the experiment, their answers on entry and exit questionnaires administered before and after the experiment, and their performance during the experiment.

We describe the characteristics of the resulting employee pool in table 2. Subsequently, all variables relating to employers are distinguished with a prefix EMP. Table 3 shows the characteristics of the employer pool which are very similar to those of the worker pool.

Variables UNIV1, UNIV2, and UNIV3 are dummy variables that denote the particular campus at which employee subjects were studying, UNT, UNSTA, and UTN, respectively. Almost 85 % of our workers came from the large public UNT university.

About 56% of the employee subject pool was male summarized by a dummy variable MALE which takes on values 0 for females and 1 for males. Variable AGE records the age of subjects. The average age in the sample is 22.9. While there were both undergraduate and graduate students in the employee subject pool, both age and undergraduate matriculation year (MATRIC) suggest that there were more graduate students. Subjects' intended or actual majors are summarized by variables COURSE_BIZ, COURSE_SCIENCE, COURSE_IT, COURSE_HUMAN, COURSE_MED, COURSE_ARTS indicating whether subjects concentrate on business, science, information technology, humanities, medicine, or arts. About 33% of subjects are from arts and humanities; 46% are from sciences, medicine and computers, and 21% are from business (including economics). We included the indicator variable INTERNET which takes a value of 1 if a subject has access to Internet at home as a rough indicator for a subject's family wealth because only households with a computer can dial-up from home. In Argentina personal computer ownership is lower than in the US which makes this a reasonable proxy for income.[11] On average, about 51% of subjects reported Internet access at home. Not surprisingly, 80% of subjects from UNSTA, a private university had access to Internet, compared to 45% for subjects at the public universities. We asked

[11] International Telecommunications Union estimates that there were 1,120 internet users in Argentina per 10,000 inhabitants in 2002, while in the US there were 5,375 users per 10,000 inhabitants. This statistic of course does not distinguish between the place of access (http://www.itu.int/ITU-D/ict/statistics/at_glance/Internet02.pdf).

our subjects about their participation in team sports since it could have a positive impact on interpersonal communication skills and confidence. This information is recorded in the variable TEAMSPORT with 1 indicating previous participation. Approximately 61% of subjects had such experience.

The number of previous jobs held by a subject are captured by PREVJOBS and the number of job interviews by INTERVIEWS. About 43% of subjects had no previous work experience and 63% of those never interviewed for a job. We expect subjects with field experience in job hunting and working to also perform more effectively in the laboratory labor market negotiations. The nature of previous employment for those with work experience is denoted by variables JOB_EDUC, JOB_IT, JOB_RETAIL, JOB_BIZ, JOB_GOV, JOB_ART, JOB_FOOD, JOB_IND indicating employment in education (20 percent of subjects with some previous work experience), information technology (7 percent), retail sales (27 percent), business (20 percent), public sector (11 percent), arts (11 percent), food production and service (2 percent) , and industry (2 percent). INTERACTION_DEGREE is a variable that describes the intensity of interpersonal interactions required in each job on a scale from 0 to 5, 0 implying no interactions and 5 being the most intense as for a secretary or a waiter. Again previous experience with interpersonal interactions is likely to improve negotiation outcomes.

We collected information on subjects' interests and hobbies. This information was coded using HOBBY_IT for computers, HOBBY_REC for recreation (e.g. watching TV or listening to music), HOBBY_CREA for creative tasks (e.g., writing, drawing, or composing music), HOBBY_SPORT for sports. If a subject reported several hobbies that were of the same category, the number of hobbies were added up and a total score reported. For example, writing, drawing and composing music was assigned a value of 3 for HOBBY_CREA. No hobbies in a certain category resulted in an entry of 0.

Table 4 shows the practice and actual performance as well as the confidence of workers. The average maze during the 15 minute trial took 94 seconds to solve whereas the practice maze took on average 127 seconds. We find that subjects were systematically underconfident: their self-estimated ability is on average 24 percent below their actual ability.

For our analysis we work with the log ability LNACTUAL and log confidence LNESTIMATED. This makes our results easier to interpret because estimated coefficients are elasticities. PREDICT is the log of the extrapolated number of rounds using the practice time:[12]

$$PREDICT = ln\left(\frac{15 \times 60}{PRACTICE}\right) \tag{4}$$

Table 5 finally shows the wage and log-wage of employers. Since every employer evaluates 5 workers and there are 165 employers all together we have 825 data points. SETWAGE is a dummy variable which is set to 1 if the employer actually determines the wage of the worker and is 0 if the worker receives an average wage.

[12]The mean value of PREDICT is larger than LNACTUAL suggesting that the extrapolated performance exceeds actual performance. However, this is just a consequence of Jensen's inequality. PRACTICE is a much more noisy estimate of ability than ACTUAL because it involves just a single maze. Since PREDICT is a convex transformation of PRACTICE we would expect an upward bias when taking the expected value.

5.2 Measuring Beauty

We follow Biddle and Hamermesh (1998) in having pictures of all 330 subjects evaluated by a group of independent evaluators on a scale of 1 to 5 (plain to above average beautiful). Our evaluators were 50 high school students from Tucuman. We presented our evaluators with the same facial photographs which were previously shown to employers in the three treatments P, PT and FTF.

The average interitem covariance for the raters was 0.349 and the scale reliability coefficient was $\alpha = 0.9596$ which both compare favorably to Biddle and Hamermesh (1998). However, rather than define BEAUTY of each subject simply as the mean rating of all our raters we instead normalize the ratings first. Formally, for each rater i we take her average beauty rating $\hat{r}_i$ and subtract it from each raw rating r_{ij} for subject j in order to define the centered rating $\tilde{r}_{ij} = r_{ij} - \hat{r}_i$. The measure BEAUTY for subject j is then defined as the mean over all raters' centered ratings:

$$BEAUTY_j = \frac{\sum_i \tilde{r}_{ij}}{\#Raters} \tag{5}$$

Effectively, this procedure strips out the measurement error which arises because each rater has a distinct definition of 'baseline' beauty: the mean ratings have a standard deviation of 0.66 while the standard deviation of the raw beauty measure is 1.23 units. Therefore this baseline error is quite large compared to the total variation in ratings. The normalized beauty measure on the other hand only has a standard deviation of 1.04.

Our results all go through if we use the raw beauty measure: however, the estimated coefficients are slightly smaller and the standard errors slightly bigger as one would expect from using a more noisy measure of physical attractiveness.

We finally normalize the beauty measure by dividing through the standard error. This allows us to interpret the coefficients on BEAUTY in our regressions as the effect of a one-standard deviation increase in physical attractiveness.

5.3 Ability and Beauty

We first analyze the determinants of maze solving ability to check whether physical attractiveness has any effect. For that purpose we regress as shown in table 6 actual productivity measured by LNACTUAL on the demographic variables AGE, MALE, family wealth (proxied by INTERNET), university dummies and physical attractiveness. Column (3) excludes subjects' decision variables such as team sports, hobbies and job experience and column (4) includes these controls.

Not accounting for differences in decision variables allows us to estimate the gross effect of physical attractiveness on ability. If decision variable controls are uncorrelated with beauty, both specifications give the same result. However, if beauty is correlated with decision variables the effect of beauty on ability might be transmitted through other channels such as a subject's choice of college major.[13]

The estimated coefficients are quite similar for both specifications. The significant variables are gender and having internet at home. Men do more than 30 percent better than women. This can be seen also by looking at summary statistics: men solved 10.9 mazes on average while women only solved 7.8 mazes during the 15 minute trial. Our gender gap is smaller than the gender gap in the mixed tournament treatment (15 versus 10.8) documented by Gneezy, Niederle, and Rustichini

[13] For example, beautiful subjects might sort into ambitious majors which improve their cognitive abilities.

(2002)[14]. The positive coefficient on INTERNET could reflect greater familiarity with using computers rather than a direct effect of wealth. Worker's age has no effect on his overall productivity.

Importantly, physical attractiveness does not raise productivity. Therefore at least for our task any measured beauty premium cannot be an ability premium. We get similar results when we analyze the performance in the practice round in table 7: men do better in the practice round and beauty does not matter. Additionally, older subjects do better (there are decreasing returns to age since AGE*AGE has a negative coefficient). A possible explanation for the age effect might be that older subjects are more experienced with taking tests and tackling unfamiliar problems. However, during the 15 minute practice less experienced subjects catch up such that age is no longer significant when we replace practice performance PREDICT with actual performance LNACTUAL in table 6.

Practice performance does predict actual ability but is clearly a noisy predictor. In columns (1) and (2) of table 6 we include PREDICT with and without controls for decision variables into our ability regression and find that a one percent increase in practice performance translates into a 0.18 and 0.16 percent increase in actual productivity. MALE is still very significant and almost as large as in regressions (3) and (4). This implies that men improve faster at the maze solving task even after controlling for their superior performance in the practice round.

[14] At the same time, our gender gap is larger than the corresponding gap of 1.5 observed by Gneezy, Niederle, and Rustichini (2002) in their piece rate treatment (11.23 versus 9.73), but in their sample this difference was not significant at 5% level.

5.4 Confidence and Beauty

In table 8 we show the results from regressions of confidence measured by the estimated number of rounds on demographic variables, practice performance and physical attractiveness. In column (2) we also control for actual ability LNACTUAL and in columns (3) and (4) we add CV controls for the verbal parts of the resume.

In all four specifications BEAUTY increases confidence. The effect is large: one standard deviation increase in BEAUTY raises confidence by 12 to 13 percent.

The coefficient on PREDICT is close to 1 in all specifications indicating that subjects do extrapolate from their performance in the practice round. In particular, the coefficient on PREDICT is much larger than the estimated coefficients in the actual ability regression of table 6.

In the first specification of column (1) male subjects seem more confident than female subjects. However, once we control for actual ability the effect disappears - men are not more confident compared to women at least when estimating their ability at solving mazes.

Moreover, physical attractiveness raises confidence for men and women equally as column (4) shows: the interaction term between BEAUTY and MALE is not significant.

6 Decomposing the Beauty Premium

We start by showing that there is a substantial gross beauty premium in treatments P, T, PT, and FTF where employers have visual and/or verbal interaction with the worker. We then decompose this beauty premium and distinguish between the stereotype, confidence, persuasion and direct discrimination channels as well as Becker-type discrimination. We conclude that most of the beauty premium is transmitted through the stereotype and confidence channels rather than Becker-type discrimination.

6.1 Evidence of the Beauty Premium

We have already shown in the previous section that a profit-maximizing employer should not grant a beauty premium: there is no interaction with customers or co-workers and we also do not find any evidence that the beautiful are better maze-solvers than the less physically attractive.

We run the following regression in order to estimate the beauty premium:

$$y_{ij} = \alpha_i + \beta_1 B_j + \beta_2 S_{ij} + \beta_3 S_{ij} * B_j + \gamma X_j + \epsilon_{ij} \tag{6}$$

where

$$\begin{aligned} y_{ij} &= \text{wage of worker } j \text{ set by employer } i \\ \\ \alpha_i &= \text{employer fixed effect} \\ B_j &= \text{worker j's beauty} \\ \\ S_{ij} &= \begin{array}{l}\text{dummy variable SETWAGE which is 1 iff employer j} \\ \text{determines worker i's wage directly}\end{array} \end{aligned} \tag{7}$$

$$
\begin{aligned}
X_j &= \text{a vector of worker j's CV characteristics} \\
\epsilon_{ij} &= \text{an error term } u_i|(B_j, S_{ij}, X_j) \sim N(0, \sigma^2)
\end{aligned} \tag{8}
$$

By including the dummy variable SETWAGE we can distinguish between contributions to the beauty premium arising from employers' tastes and all other channels.

At this point we have to be careful whether to include decision variables such as participation in team sports, choice of major, hobbies and previous job experience in our vector X_j of workers' characteristics. Neal and Johnson (1996) and Heckman (1998) advise not to include decision variables when estimating the effects of labor market discrimination because some of the effects of physical attractiveness might be transmitted through these decision variables. However, we are interested in decomposing the beauty premium. Our experimental design only varies the mode of interaction between worker and employer during one specific wage negotiation process but does not allow us to vary past decision variables such as participation in team sports and choice of hobbies.[15] Therefore, we follow Hamermesh and Biddle (1994) and focus on the marginal effect of looks after accounting for all the other sources of variations in earnings that are usually measured in labor economics; and it is only this marginal effect which we attempt to decompose. We calculate the gross (undecomposed) beauty premium both with and without controls for workers' past decision variables but subsequently always include all controls when

[15]One practical experimental design for accomplishing this in treatments 0 and P would be to create artificial CV's. However, the experimenter would then have to lie to employers who rate these CVs and pretend that the rated workers actually exist. It is unclear how any experimental design could vary past decision variables in treatments T, PT and FTF because employers could easily uncover inconsistencies during their verbal interaction with the worker.

we decompose the beauty premium.

We estimate the beauty premium separately for each of our five treatments to allow coefficients on covariates to change. In our 33 experimental sessions we have 33 distinct employers and each employer evaluates 5 workers. This provides 165 data points for each treatment. We use fixed effects estimation in order to control for employer fixed effects α_i.

Table 9 shows the estimation results without controls for team sports, hobbies and job experience and table 10 presents the same results with all controls. The estimated coefficients are similar for both regressions and we will focus on table 10.

There is no beauty premium in treatment 0 and significant beauty premia in treatments P to FTF, ranging from a 9.8 increase in wages for a one standard deviation increase in beauty in treatment P, to a 12 to 13 percent increase in treatments T and PT and a 17 percent increase in treatment FTF. These numbers are of a similar order of magnitude as the beauty premia found by Hamermesh and Biddle (1994) in their cross-sectional analysis of North American wage data. What is interesting is that there is a beauty premium in treatment T where workers can only interact verbally but not visually with the employer. Moreover, in face-to-face communication with the employer the beauty premium is significantly larger. Both of these facts suggest that beauty is correlated with certain characteristics which raise workers' wages when there is verbal interaction.

We do not find any evidence for Becker-type discrimination: the coefficient on SETWAGE*BEAUTY is not significant in any of the five regressions. This does not imply that discrimination based on employers' tastes is necessarily unimportant in real world labor markets: if employers derive utility from interacting with an attractive employee over an extended period of time our experimental design cannot account for this effect. All we can show is that employers who interact personally with an employee only during the experimental wage negotiation process do not set higher wages because they derive utility from setting higher wages for good-looking workers.

We will discuss the other significant covariates such as gender and practice performance in the next section when we start to decompose the beauty premium.

6.2 Decomposition I - Controlling for Confidence

As shown in the previous section beauty raises confidence considerably. This raises two questions:

1. Does greater confidence increase wages?
2. How much of the beauty premium can be explained because more attractive subjects are also more confident?

To analyze these two questions we include our confidence measure LNESTIMATED in our wage regressions and estimate the following extended specification:

$$y_{ij} = \alpha_i + \beta_1 B_j + \beta_2 S_{ij} + \beta_3 S_{ij} * B_j + \beta_4 C_j + \beta_5 S_{ij} * B_j + \gamma X_j + \epsilon_{ij} \tag{9}$$

where

$$C_j \quad = \quad \text{worker j's confidence} \tag{10}$$

We interact confidence with SETWAGE to control for employers' tastes for confident workers.

The estimation results are shown in table 11. First of all, we note that there is a significant return to confidence in treatments T, PT and FTF where workers can interact verbally with employers. We do not find a confidence premium in treatments 0 and P which is consistent with the fact that these are the only treatments where the employer cannot interact verbally with the workers. A one percent increase in confidence increases wages by about 0.2 percent in treatments T and PT and .3 percent in treatment FTF.

Hamermesh and Biddle (1994) include measures of self-esteem in their wage cross-sectional regressions and find that these measures are significant just as the confidence variable is in our analysis. However, there is little effect on the size of the beauty premium in their estimation and only a weak correlation between beauty and self-esteem. These differences can be explained by greater measurement error of confidence. Hamermesh and Biddle (1994) have to rely on a psychometric measure of general self-esteem in their survey data whereas we can extract a cardinal measure of confidence in solving the specific experimental task with a natural scale. Furthermore, our experimental setup allows us to interpret the coefficient on confidence as a causal effect rather than a correlation coefficient: we do not have to worry about reverse causality such that more highly paid subjects enjoy greater self-esteem. Finally, the fact that confidence only matters in the treatments with verbal interaction indicates that our confidence measure is not just a proxy for omitted variables.

The beauty premia in treatments P to FTF decline when we control for confidence but are still significantly different from 0. This suggests that at least part of the beauty premium is transmitted through greater confidence of physically attractive workers. We can decompose the beauty premium in treatments T, PT and FTF by using the following back of the envelope calculation. One standard deviation in beauty increases confidence by about 12 percent according to our regression results in table 8 (we assume SETWAGE is zero for simplicity). In treatment T a one percent increase in confidence increases wages by 0.20 percent. Therefore, the total increase in wages of a one standard deviation increase in beauty which is transmitted through the confidence channel is:

$$12 \times 0.20 \quad \text{percent} = 2.4 \quad \text{percent} \tag{11}$$

The residual beauty premium after controlling for confidence in treatment T is 8.7 percent for a one standard deviation increase in beauty. The sum of both effects is 11.1 percent which is reasonably close to the gross beauty premium of 12.8 percent that we estimated for treatment T. Table 1 presents the same decomposition for treatments PT and FTF. These results suggest that under verbal communication between 17 and 25 percent of the beauty premium is transmitted through an increase in confidence.

SETWAGE has no effect on its own or when interacted with BEAUTY or LNESTIMATED except in treatment FTF where more confident subjects whose wage is set by the evaluator receive a lower wage. As before we therefore find no evidence for the presence of direct taste based discrimination against the less beautiful.

Table 1: Contribution of confidence channel to gross beauty premium in treatments T, P and FTF

Treatment	Beauty Premium (controlled for confidence)	Confidence Channel	Gross Beauty Premium
T	8.7	2.4	12.8
PT	10.1	2.1	12.3
FTF	12.1	4.0	16.6

The entries are wage increases in percentage points for each one standard deviation increase in beauty. They are calculated using the estimated coefficients in tables 10 and 11. SETWAGE is assumed to be zero.

We attribute the estimated residual beauty premia in table 11 to the direct and indirect stereotype channels which make the beautiful appear more able in the eyes of the employer. The direct stereotype effect (treatment P) raises wages by about 10.5 percent for each one standard deviation increase in beauty when employers only see a picture of the worker. Interestingly, there is also a strong indirect stereotype effect even in treatment T where employers have no visual information about the worker but only interact verbally over the phone. This suggests that beauty is correlated with certain verbal skills other than confidence which raise employers' expectations about a worker's ability. These stereotype effects do not seem additive: in treatments PT and FTF where employers and workers interact both visually and verbally the beauty premia are only marginally greater but not significantly so.

We also test whether the beauty premium is non-linear. Hamermesh and Biddle (1994) found that the 'plainness' penalty is slightly bigger than the premium on being of above average beauty. To replicate their analysis we divide our workers into three groups of equal size - the 'below-average-looking', the 'average-looking' and the 'above-average-looking'. BEAUTYHIGH is set to 1 if the worker is above average looking and 0 otherwise. Similarly, BEAUTYLOW indicates below-average looks. Table 12 shows the modified regression 9 where we replace BEAUTY by BEAUTYHIGH and BEAUTYLOW. We lose power but the coefficients on BEAUTYHIGH and BEAUTYLOW are of the correct sign. We cannot reject the hypothesis in any treatment that the coefficients are equal. We therefore do not find evidence for significant non-linearity in the stereotype beauty premium.

6.3 Decomposition II - Controlling for Persuasion

The persuasion channel is another, more subtle channel through which a beautiful worker can obtain higher wages than a less beautiful worker with the same confidence level: the beautiful worker might be more successful in persuading the employer about his ability than his less good-looking counterpart.

To test for the presence of persuasion effects we interact BEAUTY with confidence and estimate the following model:

$$y_{ij} = \alpha_i + \beta_1 B_j + \beta_2 S_{ij} + \beta_3 S_{ij} * B_j + \beta_4 C_j + \beta_5 S_{ij} * B_j + \beta_6 C_j * B_j + \gamma X_j + \epsilon_{ij} \quad (12)$$

If the beautiful are indeed more persuasive than the less beautiful we would expect the estimated coefficient β_6 to be positive in treatments T, PT and FTF.

Table 17 shows that the interaction term is insignificant in all treatments. We find no support for the persuasion channel in our data.

6.4 Effects of Other Covariates

It is instructive to look more closely at the estimates for the other covariates in the regression summarized in table 11. Except for confidence and physical attractiveness only the practice performance is consistently significant.

1. A one percent increase in practice performance raises wages by about .4 percent in treatments 0 and P and .3 percent in treatments T, PT and FTF. While not statistically significant at the 5 percent level the decline is nevertheless consistent with the hypothesis that employers put less emphasis on practice performance when they can also interact verbally with the worker.

2. Actual ability (measured by LNACTUAL) is *not* statistically significant in any treatment - in particular in treatments T, PT, and FTF where employers can interact verbally with workers. At least in our experiment, employers seem to be unable to ascertain actual ability during the verbal interview process. This is quite surprising given that employers do seem to attach a large weight to worker's confidence.

3. Neither participation in team sports nor having internet at home affects the wage level in any treatment.

6.5 Gender Effects

Do male workers get higher wages? The evidence from table 11 provides weak evidence for this hypothesis: in treatments T and PT male workers do get 12 to 18 percent higher wages but not in the other treatments (even though all coefficients are positive).

We next check whether the confidence and stereotype effects are gender-specific. There are two type of gender effects we have to consider - the gender of the employer and the gender of the worker. To take all possible interactions into account we run regression 9 for male and female employers separately in tables 13 and 14. We also include interaction terms between BEAUTY and MALE to control for worker gender effects. We lose a lot of power due to reduced sample especially for the female employer regression in table 14.

The beauty and confidence effects seem to be slightly bigger for male employers. However, the gender of the worker has little effect for the wage setting of both male and female employers.

6.6 Does Employer Beauty Matter?

We also test whether the beauty of the employer matters. For this purpose we run regression 9 separately for employers of below average beauty (EMPBEAUTY<0) and those of above average beauty (EMPBEAUTY>0). The results are presented in tables 16 and 15.

The estimated coefficients on BEAUTY are slightly more significant for more beautiful employers even though they are of similar magnitude for all employers. There is little difference in the estimated coefficients on confidence.

6.7 Decomposition III - Pooled Regression

In order to compare the direct and indirect stereotype channels as well as confidence premium we estimate a unified model in table 18. For this purpose we introduce three new dummy variables which code the mode of interaction for each treatment.

AUDIO is set to 1 if the worker and employer can talk to each other (treatments T,PT and FTF). VISUAL is set to 1 if the employer can see the worker's picture (treatments P, PT and FTF). Finally, FTF is set to 1 if there is face-to-face communication (treatment FTF).

We interact PREDICT, BEAUTY and LNESTIMATED with these dummies and include all CV controls in the regression. The direct stereotype channel is identified by the coefficient on BEAUTY*VISUAL which is 7.2 percent wage gain for each one standard deviation in beauty. The indirect stereotype channel is captured by BEAUTY*AUDIO which is 10.4 percent. The confidence channel raises the wage by 0.3 percent for each one percent increase in confidence. This translates into a 3.6 percent increase in wagesfor a one standard deviation increase in beauty.

Taken together, results from pooled regression imply that about 20 percent of the beauty premium is due to the increased confidence of beautiful subjects, 50 percent due to indirect stereotypes and 30 percent due to direct stereotypes.

It is of interest to note the difference between treatments PT and FTF. The total beauty premium in treatment PT (photograph and telephone) is slightly less than the sum of the direct and indirect stereotype channels while in treatment FTF (face-to-face communication) the beauty premium is slightly larger than the sum (although not significantly so). In contrast, the confidence premium has similar strength in all three treatments where there is verbal interaction between worker and employer.

7 Conclusion

In this paper, we constructed an experimental labor market in order to study the effects of physical attractiveness on wage setting. We find that about four fifths of the beauty premium is due to direct and indirect stereotypes and about one fifth due to the enhanced confidence of good-looking subjects. As with a vast body of experimental studies, standard criticisms of our student subject pool apply. It is conceivable that real-world human resource managers have a more extensive experience in screening applicants and might be less susceptive to physical features of the applicants. We view our results as complementary to the existing literature which uses real data starting with Hamermesh and Biddle (1994). While this empirical literature identified a beauty premium, our experimental approach allows us to conduct a detailed study of the possible transmission mechanisms. Even though we have to be cautious in drawing direct parallels to the real-world phenomena, we find it encouraging that our experiment does generate a sizable beauty premium of the right order of magnitude. This makes us confident that our decomposition applies more generally.

Another important caveat is that we only model the interview process. If employer and worker interact repeatedly over the long-term Becker-type discrimination might again become a more important contributor to the beauty premium and stereotype and confidence effects might become less relevant.

If one is willing to extrapolate from our experiment to the labor market more generally we can draw two main policy implications. First, 'blind' interview procedures such as telephone interviews can reduce the beauty premium by about

30 percent[16]. Interestingly, this reduction is not due to the elimination of taste-based discrimination against the less beautiful but due to the absence of direct stereotypes effects. Second, the biggest reduction of the beauty premium would result from preventing verbal interaction between employer and employee. Our results suggest that removing both verbal and visual interaction might eliminate the beauty premium all together. However, such a drastic policy would likely decrease the quality of job matches along other dimensions.

References

Adams, G. (1977a): "Physical Attractiveness, Personality, and Social Reactions to Peer Pressure," *Journal of Psychology*, 96, 287–296.

——— (1977b): "Physical Attractiveness Research: Towards a Developmental Social Psychology of beauty," *Human Development*, 20, 217–239.

Biddle, J. E., and D. S. Hamermesh (1998): "Beauty, Productivity, and Discrimination: Lawyers' Looks and Lucre," *Journal of Labor Economics*, 16(1), 172–201.

Bull, R., and J. Stevens (1981): "The Relationship between Ratings of Persons' Facial Appearance and Ratings of Their Conversations," *Language and Speech*, 24, 285–291.

Cassidy, T., and C. Long (1996): "Problem-solving style, stress and psychological illness: Development of a multifactorial measure," *British Journal of Clinical Psychology*, 35, 265–277.

Chaiken, S. (1979): "Communicator Physical Attractiveness and Persuasion," *Journal of Personality and Social Psychology*, 37, 1387–1397.

Eagly, A. H., R. D. Ashmore, M. G. Makhijani, and L. C. Longo (2001): "What is Beautiful is Good, But: A Meta-Analytic Review of Research on the Physical Attractiveness Stereotype," *Journal of Management*, 27, 363–381.

[16] Similarly, Goldin and Rouse (2000) find that 'blind' auditions increase the probability of female musicians being hired or promoted.

FEINGOLD, A. (1992): "Good-Looking People Are Not What We Think," *Psychological Bulletin*, 111, 304–341.

GNEEZY, U., M. NIEDERLE, AND A. RUSTICHINI (2002): "Performance in Competitive Environments: Gender Differences," *Quarterly Journal of Economics forthcoming*.

GOLDIN, C., AND C. ROUSE (2000): "Orchestrating Impartiality: The Effect of 'Blind' Auditions on Female Musicians," *American Economic Review*, 90.

GOLDMAN, W., AND P. LEWIS (1977): "Beautiful is Good: Evidence that the Physically Attractive are More Socially Skillful," *Journal of Experimental Social Psychology*, 13, 125–130.

HAMERMESH, D. S., AND J. E. BIDDLE (1994): "Beauty and the Labor Market," *The American Economic Review*, 84(5), 1174–1194.

HAMERMESH, D. S., M. XIN, AND Z. JUNSEN (1999): "Dress for Success - Does Primping Pay?," Working paper 7167, NBER.

HATFIELD, E., AND S. SPRECHER (1986): *Mirror, Mirror ...: The Importance of Looks in Everyday Life*. SUNY Press, Alabany.

HECKMAN, J. J. (1998): "Detecting Discrimination," *Journal of Economic Perspectives*, 12, 101–116.

——— (2000): "Policies to Foster Human Capital," *Research in Economics*, 54, 3–56.

HEMSLEY, G. D., AND A. N. DOOB (1978): "The Effect of Looking Behavior on Perceptions of a Communicator's Creidbility," *Journal of Applied Social Psychology*, 8, 136–144.

JACKSON, L. A., J. E. HUNTER, AND C. N. HODGE (1995): "Physical Attractiveness and Intellectual Competence: A Meta-Analytic Review," *Social Psychology Quarterly*, 58, 108–122.

KAHN, A., J. HOTTES, AND W. L. DAVIS (1971): "Cooperation and Optimal Responding in the Prisoner's Dilemma Game: Effects of Sex and Physical Attractiveness," *Jounal of Personality and Social Psychology*, 17, 267–279.

LORR, M., AND R. A. WUNDERLICH (1986): "Two objective measures of self-esteem," *Journal of Personality Assessment*, 50, 18–23.

Mittag, W., and R. Schwarzer (1993): "Interaction of employment status and self-efficacy on alcohol consumption: A two-wave study on stressful life transitions," *Psychology & Health*, 8, 77–87.

Mulford, M., J. Orbell, C. Shatto, and J. Stockard (1998): "Physical Attractiveness, Opportunity and Success in Everyday Exchange," *The American Journal of Sociology*, 103, 1565–1593.

Neal, D., and W. Johnson (1996): "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, 104, 869–95.

Persico, N., A. Postlewaite, and D. Silverman (2001): "The Effect of Adolescent Experience on Labor Market Outcomes: The Case of Height," Discussion paper, mimeo.

Pfann, G. A., C. M. Bosman, J. E. Biddle, and D. S. Hamermesh (2000): "Business Success and Business Beauty Capital," *Economic Letters*, 67(2), 201–07.

Solnick, S. J., and M. E. Schweitzer (1999): "The Influence of Physical Attractiveness and Gender on Ultimatum Game Decisions," *Organizational Behavior and Human Decision Processes*, 79(3), 199–215.

Straus, S. G., J. A. Miles, and L. L. Levesque (2001): "The Effects of Videoconference, Telephone and Face-To-Face Media on Interviewer and Applicant judgements in Employment Interviews," *Journal of Management*, 27, 363–381.

Table 2: Summary statistics - workers

Variable	Mean	Std. Dev.	Min.	Max.	N
Demographic Variables					
AGE	22.963	3.212	18	48	164
MALE	0.564	0.497	0	1	165
MATRIC	1998.317	2.784	1984	2003	164
UNIV1	0.848	0.36	0	1	165
UNIV2	0.091	0.288	0	1	165
UNIV3	0.061	0.239	0	1	165
INTERNET	0.515	0.501	0	1	165
TEAMSPORT	0.612	0.489	0	1	165
Job Experience					
INTERVIEWS	1.267	1.303	0	4	165
PREVJOBS	1.188	1.337	0	4	165
JOB_EDUC	0.067	0.25	0	1	165
JOB_IT	0.024	0.154	0	1	165
JOB_RETAIL	0.091	0.288	0	1	165
JOB_BIZ	0.067	0.25	0	1	165
JOB_GOV	0.036	0.188	0	1	165
JOB_ART	0.036	0.188	0	1	165
JOB_FOOD	0.006	0.078	0	1	165
JOB_IND	0.006	0.078	0	1	165
INTERACTION_DEGREE	0.636	1.357	0	5	165
Course of Study					
COURSE_BIZ	0.207	0.407	0	1	164
COURSE_SCIENCE	0.134	0.342	0	1	164
COURSE_IT	0.22	0.415	0	1	164
COURSE_HUMAN	0.244	0.431	0	1	164
COURSE_MED	0.104	0.306	0	1	164
COURSE_ARTS	0.091	0.289	0	1	164
Hobbies					
HOBBY_IT	0.273	0.46	0	2	165
HOBBY_REC	0.855	0.791	0	3	165
HOBBY_CREA	0.830	0.746	0	3	165
HOBBY_SPORT	0.655	0.738	0	3	165
Physical Attractiveness					
BEAUTY	0.024	1.001	-1.677	3.066	165

Table 3: Summary statistics - employers

Variable	Mean	Std. Dev.	Min.	Max.	N
Demographic Variables					
EMP_AGE	22.673	2.482	18	30	162
EMP_MALE	0.604	0.491	0	1	164
EMP_MATRIC	1998.659	2.364	1990	2003	164
EMP_UNIV1	0.902	0.298	0	1	164
EMP_UNIV2	0.061	0.24	0	1	164
EMP_UNIV3	0.037	0.188	0	1	164
EMP_INTERNET	0.482	0.501	0	1	164
EMP_TEAMSPORT	0.604	0.491	0	1	164
Job Experience					
EMP_INTERVIEWS	1.268	1.357	0	4	164
EMP_PREVJOBS	1.128	1.239	0	4	164
EMP_JOB_EDUC	0.067	0.25	0	1	165
EMP_JOB_IT	0.03	0.172	0	1	165
EMP_JOB_RETAIL	0.048	0.215	0	1	165
EMP_JOB_BIZ	0.121	0.327	0	1	165
EMP_JOB_GOV	0.042	0.202	0	1	165
EMP_JOB_ART	0.024	0.154	0	1	165
EMP_JOB_FOOD	0.018	0.134	0	1	165
EMP_JOB_IND	0.012	0.11	0	1	165
EMP_INTER_DEGREE	0.818	1.503	0	5	165
Course of Study					
EMP_COURSE_BIZ	0.239	0.428	0	1	163
EMP_COURSE_SCIENCE	0.135	0.343	0	1	163
EMP_COURSE_IT	0.153	0.361	0	1	163
EMP_COURSE_HUMAN	0.252	0.435	0	1	163
EMP_COURSE_MED	0.117	0.322	0	1	163
EMP_COURSE_ARTS	0.104	0.307	0	1	163
Hobbies					
EMP_HOBBY_IT	0.212	0.425	0	2	165
EMP_HOBBY_REC	0.933	0.79	0	3	165
EMP_HOBBY_CREA	0.873	0.717	0	3	165
EMP_HOBBY_SPORT	0.539	0.685	0	3	165
Physical Attractiveness					
EMP_BEAUTY	0.026	1	-1.979	2.572	165

Table 4: Summary statistics - productivity

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
		Raw Variables			
PRACTICE	126.691	92.068	13	605	825
ESTIMATED	7.255	4.003	1	23	825
ACTUAL	9.527	3.864	1	21	825
		Log-Variables			
PREDICT	2.225	0.762	0.397	4.237	825
LNESTIMATED	1.829	0.571	0	3.135	825
LNACTUAL	2.149	0.503	0	3.045	825

Table 5: Summary statistics - wages

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
		Raw Variables			
WAGE	7.747	5.187	1	51	822
SETWAGE	0.531	0.499	0	1	825
		Log-Variables			
LNWAGE	1.865	0.611	0	3.932	822

Table 6: The impact of practice performance and beauty on maze solving ability

Variable	(1)	(2)	(3)	(4)
AGE	0.027	0.038	0.072	0.081
	(0.058)	(0.064)	(0.059)	(0.065)
AGE*AGE	-0.001	-0.001	-0.002†	-0.002†
	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.318**	0.303**	0.369**	0.331**
	(0.073)	(0.081)	(0.076)	(0.086)
UNIV2	-0.087	-0.088	-0.137	-0.113
	(0.126)	(0.139)	(0.131)	(0.143)
UNIV3	0.198	0.115	0.174	0.042
	(0.146)	(0.197)	(0.152)	(0.201)
INTERNET	0.099	0.136†	0.123	0.158†
	(0.071)	(0.080)	(0.076)	(0.083)
BEAUTY			-0.037	-0.034
			(0.038)	(0.042)
TEAMSPORT		0.054		0.062
		(0.085)		(0.088)
PREDICT	0.181**	0.160**		
	(0.049)	(0.054)		
PREVJOBS		0.052		0.057
		(0.036)		(0.037)
CV controls	No	Yes	No	Yes
N	164	163	164	163
R^2	0.281	0.362	0.221	0.323

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The dependent variable is LNACTUAL; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience.

Table 7: The impact of beauty on practice performance

Variable	(1)	(2)
AGE	0.286**	0.345**
	(0.093)	(0.100)
AGE*AGE	-0.005**	-0.006**
	(0.002)	(0.002)
MALE	0.439**	0.344*
	(0.121)	(0.132)
UNIV2	-0.229	-0.095
	(0.206)	(0.220)
UNIV3	-0.148	-0.425
	(0.239)	(0.310)
INTERNET	0.031	0.043
	(0.119)	(0.128)
BEAUTY	0.070	0.078
	(0.060)	(0.065)
TEAMSPORT		-0.013
		(0.136)
Intercept	-2.011	-2.641†
	(1.316)	(1.444)
CV controls	No	Yes
N	164	163
R^2	0.132	0.277

Significance levels: † : 10% $*$: 5% $**$: 1%

The dependent variable is PREDICT; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience.

Table 8: The impact of beauty on confidence

Variable	(1)	(2)	(3)	(4)
AGE	0.046	0.043	0.018	0.018
	(0.055)	(0.054)	(0.060)	(0.060)
AGE*AGE	-0.001	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.142†	0.100	0.015	0.015
	(0.072)	(0.075)	(0.080)	(0.081)
UNIV2	0.052	0.066	0.035	0.036
	(0.119)	(0.118)	(0.127)	(0.128)
UNIV3	-0.073	-0.103	-0.183	-0.184
	(0.137)	(0.137)	(0.179)	(0.180)
INTERNET	0.096	0.078	0.042	0.042
	(0.068)	(0.068)	(0.074)	(0.075)
TEAMSPORT			0.127	0.128
			(0.078)	(0.079)
PREDICT	0.470**	0.443**	0.429**	0.429**
	(0.046)	(0.048)	(0.051)	(0.051)
LNACTUAL		0.146†	0.177*	0.177*
		(0.075)	(0.078)	(0.079)
BEAUTY	0.134**	0.141**	0.135**	0.133**
	(0.035)	(0.035)	(0.038)	(0.051)
BEAUTY*MALE				0.002
				(0.075)
PREVJOBS			-0.003	-0.003
			(0.033)	(0.033)
CV controls	No	No	Yes	Yes
N	164	164	163	163
R^2	0.509	0.521	0.587	0.587

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The dependent variable is LNESTIMATED; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience.

Table 9: The impact of beauty on wages in treatments (0) to (FTF) (no CV controls)

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	-0.002	-0.013	-0.009	$0.072^{\dagger}$	-0.091^{*}
	(0.046)	(0.039)	(0.037)	(0.038)	(0.044)
AGE*AGE	0.000	0.000	0.000	$-0.001^{\dagger}$	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.048	0.077	0.106^{*}	0.190^{**}	0.026
	(0.065)	(0.057)	(0.053)	(0.053)	(0.063)
UNIV2	$0.171^{\dagger}$	0.089	0.022	-0.091	-0.017
	(0.102)	(0.087)	(0.082)	(0.083)	(0.099)
UNIV3	0.083	0.127	0.041	-0.248^{*}	0.005
	(0.125)	(0.108)	(0.102)	(0.102)	(0.124)
INTERNET	0.021	-0.046	0.137^{**}	0.025	0.066
	(0.059)	(0.052)	(0.048)	(0.049)	(0.058)
PREDICT	0.388^{**}	0.391^{**}	0.382^{**}	0.369^{**}	0.332^{**}
	(0.042)	(0.036)	(0.034)	(0.035)	(0.041)
LNACTUAL	-0.017	0.041	-0.023	0.136^{*}	-0.003
	(0.063)	(0.055)	(0.051)	(0.055)	(0.061)
BEAUTY	0.017	0.114^{**}	0.111^{**}	0.094^{**}	0.127^{**}
	(0.041)	(0.039)	(0.033)	(0.033)	(0.039)
SETWAGE	-0.022	-0.070	$0.075^{\dagger}$	-0.032	0.046
	(0.055)	(0.050)	(0.045)	(0.044)	(0.054)
SETWAGE*BEAUTY	-0.070	-0.073	0.004	0.033	-0.015
	(0.055)	(0.051)	(0.046)	(0.046)	(0.055)
CV controls	No	No	No	No	No
N	164	162	164	163	164
R^2	0.485	0.613	0.663	0.707	0.514

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. All regressions include employer fixed effects.

Table 10: The impact of beauty on wages in treatments (0) to (FTF)

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	0.001	-0.001	-0.020	0.080*	-0.117*
	(0.047)	(0.042)	(0.038)	(0.040)	(0.047)
AGE*AGE	0.000	0.000	0.000	-0.001*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.062	0.082	0.139*	0.191**	0.078
	(0.070)	(0.063)	(0.056)	(0.059)	(0.070)
UNIV2	0.152	0.083	0.085	-0.090	0.050
	(0.105)	(0.094)	(0.084)	(0.088)	(0.106)
UNIV3	0.319*	0.104	-0.136	-0.346**	0.150
	(0.151)	(0.138)	(0.124)	(0.129)	(0.155)
INTERNET	0.050	-0.020	0.071	-0.004	0.056
	(0.065)	(0.058)	(0.052)	(0.055)	(0.065)
TEAMSPORT	-0.004	-0.023	-0.030	-0.009	-0.042
	(0.067)	(0.059)	(0.053)	(0.055)	(0.066)
PREDICT	0.403**	0.396**	0.406**	0.374**	0.372**
	(0.043)	(0.038)	(0.035)	(0.037)	(0.043)
LNACTUAL	-0.045	0.000	-0.019	0.087	-0.014
	(0.063)	(0.057)	(0.051)	(0.057)	(0.063)
BEAUTY	0.013	0.124**	0.128**	0.123**	0.166**
	(0.040)	(0.042)	(0.034)	(0.036)	(0.043)
SETWAGE	-0.016	-0.080	0.097*	-0.048	0.033
	(0.055)	(0.052)	(0.046)	(0.048)	(0.057)
SETWAGE*BEAUTY	-0.059	-0.092†	0.001	0.015	-0.040
	(0.057)	(0.054)	(0.048)	(0.050)	(0.057)
CV controls	Yes	Yes	Yes	Yes	Yes
N	163	161	163	162	163
R^2	0.604	0.689	0.747	0.77	0.604

Significance levels: † : 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience. All regressions include employer fixed effects.

Table 11: The impact of beauty and confidence on wages in treatments (0) to (FTF)

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	0.003	-0.010	-0.029	0.076†	-0.136**
	(0.048)	(0.042)	(0.036)	(0.039)	(0.045)
AGE*AGE	0.000	0.000	0.000	-0.001*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.063	0.064	0.128*	0.184**	0.082
	(0.071)	(0.066)	(0.053)	(0.057)	(0.067)
UNIV2	0.147	0.091	0.097	-0.077	0.017
	(0.108)	(0.094)	(0.080)	(0.085)	(0.102)
UNIV3	0.316*	0.142	-0.089	-0.307*	0.102
	(0.154)	(0.142)	(0.118)	(0.126)	(0.152)
INTERNET	0.052	-0.032	0.057	-0.016	0.044
	(0.066)	(0.059)	(0.050)	(0.054)	(0.062)
TEAMSPORT	-0.004	-0.025	-0.050	-0.021	-0.066
	(0.068)	(0.060)	(0.051)	(0.053)	(0.064)
PREDICT	0.412**	0.386**	0.321**	0.297**	0.298**
	(0.053)	(0.047)	(0.040)	(0.044)	(0.050)
LNACTUAL	-0.041	0.006	-0.055	0.056	-0.044
	(0.065)	(0.059)	(0.050)	(0.055)	(0.061)
BEAUTY	0.015	0.105*	0.087*	0.101**	0.121**
	(0.042)	(0.045)	(0.035)	(0.037)	(0.043)
LNESTIMATED	-0.008	0.109	0.204**	0.179**	0.330**
	(0.098)	(0.094)	(0.065)	(0.068)	(0.096)
CV controls	Yes	Yes	Yes	Yes	Yes
N	163	161	163	162	163
R^2	0.604	0.694	0.78	0.791	0.646

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience. All regressions also include interaction terms between SETWAGE and BEAUTY and LNESTIMATED to control for direct discrimination. All regressions include employer fixed effects.

Table 12: The impact of beauty and confidence on wages in treatments (0) to (FTF) (allowing for non-linearity)

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	0.009	-0.007	-0.035	$0.068^{\dagger}$	-0.126^{**}
	(0.047)	(0.043)	(0.037)	(0.040)	(0.043)
AGE*AGE	0.000	0.000	0.000	$-0.001^{\dagger}$	0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.087	0.066	0.129^{*}	0.189^{**}	0.102
	(0.072)	(0.067)	(0.055)	(0.058)	(0.065)
UNIV2	0.146	0.090	0.082	-0.092	-0.042
	(0.107)	(0.095)	(0.081)	(0.085)	(0.098)
UNIV3	0.361^{*}	0.122	-0.096	-0.320^{*}	0.064
	(0.154)	(0.142)	(0.121)	(0.128)	(0.145)
INTERNET	0.059	-0.035	0.056	-0.022	0.045
	(0.065)	(0.060)	(0.051)	(0.054)	(0.059)
TEAMSPORT	-0.017	-0.032	-0.061	-0.037	$-0.108^{\dagger}$
	(0.068)	(0.061)	(0.052)	(0.054)	(0.061)
PREDICT	0.405^{**}	0.367^{**}	0.303^{**}	0.281^{**}	0.284^{**}
	(0.052)	(0.047)	(0.040)	(0.044)	(0.048)
LNACTUAL	-0.033	0.010	-0.052	0.061	-0.047
	(0.065)	(0.060)	(0.052)	(0.056)	(0.059)
BEAUTYHIGH	0.104	0.108	0.106	0.210^{*}	-0.008
	(0.096)	(0.096)	(0.078)	(0.090)	(0.096)
BEAUTYLOW	0.065	-0.133	-0.138	-0.041	-0.315^{**}
	(0.108)	(0.091)	(0.084)	(0.085)	(0.099)
LNESTIMATED	0.005	0.113	0.205^{**}	0.193^{**}	0.338^{**}
	(0.097)	(0.095)	(0.067)	(0.069)	(0.093)
CV controls	Yes	Yes	Yes	Yes	Yes
N	163	161	163	162	163
R^2	0.619	0.694	0.775	0.793	0.686

Significance levels: $\dagger$: 10% $\quad *$: 5% $\quad **$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience. All regressions also include interaction terms between SETWAGE and BEAUTY and LNESTIMATED to control for direct discrimination. All regressions include employer fixed effects.

Table 13: The impact of beauty and confidence on wages in treatments (0) to (FTF) including gender effects and **male** employers only

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	0.343*	0.098†	-0.113	-0.057	-0.181**
	(0.163)	(0.057)	(0.108)	(0.166)	(0.055)
AGE*AGE	-0.007*	-0.001	0.002	0.001	0.003**
	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
MALE	0.154	-0.097	0.594*	0.169	-0.045
	(0.277)	(0.309)	(0.229)	(0.260)	(0.334)
UNIV2	0.065	-0.030	0.141	0.083	0.011
	(0.134)	(0.127)	(0.103)	(0.157)	(0.157)
UNIV3	0.215	0.225	0.021	-0.071	-0.086
	(0.234)	(0.187)	(0.160)	(0.180)	(0.213)
INTERNET	-0.003	0.038	0.032	-0.082	-0.007
	(0.076)	(0.089)	(0.071)	(0.079)	(0.088)
TEAMSPORT	-0.025	-0.030	-0.148*	0.014	0.015
	(0.082)	(0.081)	(0.071)	(0.078)	(0.084)
PREDICT	0.415**	0.239**	0.268**	0.340**	0.282**
	(0.069)	(0.071)	(0.059)	(0.071)	(0.074)
LNACTUAL	-0.024	-0.047	0.068	0.011	0.075
	(0.078)	(0.079)	(0.076)	(0.083)	(0.089)
BEAUTY	-0.056	0.113*	0.094†	0.031	0.145*
	(0.049)	(0.048)	(0.051)	(0.068)	(0.058)
BEAUTY*MALE	0.066	-0.067	0.036	0.078	-0.014
	(0.093)	(0.070)	(0.080)	(0.097)	(0.089)
LNESTIMATED	0.120	0.107	0.339**	0.289*	0.081
	(0.111)	(0.106)	(0.090)	(0.116)	(0.118)
LNESTIMATED*MALE	-0.007	0.095	-0.258*	-0.037	-0.008
	(0.137)	(0.163)	(0.122)	(0.141)	(0.160)
CV controls	Yes	Yes	Yes	Yes	Yes
N	94	92	100	92	108
R^2	0.798	0.774	0.8	0.837	0.658

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience. All regressions include employer fixed effects.

Table 14: The impact of beauty and confidence on wages in treatments (0) to (FTF) including gender effects and **female** employers only

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	-0.037	-0.089	-0.083	0.186**	1.105
	(0.100)	(0.236)	(0.057)	(0.048)	(0.663)
AGE*AGE	0.000	0.002	0.001	-0.004**	-0.023
	(0.001)	(0.005)	(0.001)	(0.001)	(0.015)
MALE	0.715	0.030	0.430	0.389	-0.656
	(0.449)	(0.364)	(0.316)	(0.255)	(0.452)
UNIV2	0.302	0.265	0.256	-0.221*	-0.042
	(0.212)	(0.157)	(0.162)	(0.104)	(0.175)
UNIV3	0.399	-0.122	-0.022	-0.776**	0.614
	(0.255)	(0.257)	(0.245)	(0.245)	(0.572)
INTERNET	0.134	-0.093	0.046	0.213†	0.049
	(0.164)	(0.098)	(0.105)	(0.110)	(0.113)
TEAMSPORT	0.198	-0.180†	0.063	-0.006	-0.323*
	(0.158)	(0.097)	(0.097)	(0.074)	(0.128)
PREDICT	0.429**	0.462**	0.485**	0.204**	0.221†
	(0.108)	(0.076)	(0.092)	(0.053)	(0.113)
LNACTUAL	-0.002	0.049	-0.199*	-0.092	0.021
	(0.148)	(0.107)	(0.077)	(0.098)	(0.194)
BEAUTY	-0.084	0.033	-0.037	0.080*	0.110
	(0.107)	(0.073)	(0.048)	(0.038)	(0.069)
BEAUTY*MALE	0.080	-0.100	0.156†	0.001	-0.260
	(0.126)	(0.104)	(0.078)	(0.066)	(0.151)
LNESTIMATED	0.095	0.030	0.188	0.184†	0.098
	(0.199)	(0.168)	(0.151)	(0.099)	(0.180)
LNESTIMATED*MALE	-0.495†	0.015	-0.197	-0.022	0.456†
	(0.243)	(0.178)	(0.164)	(0.127)	(0.227)
CV controls	Yes	Yes	Yes	Yes	Yes
N	69	69	63	70	50
R^2	0.67	0.868	0.907	0.911	0.932

Significance levels: † : 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience. All regressions include employer fixed effects.

Table 15: The impact of beauty and confidence on wages in treatments (0) to (FTF) - employers of above average beauty only

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	-0.012	0.121	0.077	$0.088^{\dagger}$	-0.056
	(0.075)	(0.102)	(0.076)	(0.048)	(0.187)
AGE*AGE	0.000	-0.002	-0.001	$-0.002^{\dagger}$	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)
MALE	0.053	0.028	0.255^{*}	$0.147^{\dagger}$	0.112
	(0.132)	(0.167)	(0.112)	(0.074)	(0.111)
UNIV2	$0.354^{\dagger}$	0.143	0.113	-0.171	0.277
	(0.176)	(0.186)	(0.257)	(0.103)	(0.198)
UNIV3	0.547^{*}	-0.122	-0.729^{*}	-0.485^{*}	-0.113
	(0.250)	(0.253)	(0.290)	(0.196)	(0.268)
INTERNET	0.144	-0.104	-0.048	0.028	-0.075
	(0.109)	(0.110)	(0.118)	(0.071)	(0.097)
TEAMSPORT	0.073	0.030	-0.117	-0.008	0.009
	(0.115)	(0.126)	(0.112)	(0.070)	(0.129)
PREDICT	0.366^{**}	0.297^{**}	0.144	0.277^{**}	0.386^{**}
	(0.082)	(0.088)	(0.086)	(0.058)	(0.120)
LNACTUAL	-0.011	0.046	$0.270^{\dagger}$	0.172^{*}	-0.240
	(0.105)	(0.160)	(0.128)	(0.075)	(0.144)
BEAUTY	-0.005	0.145	0.080	0.102^{*}	$0.136^{\dagger}$
	(0.084)	(0.101)	(0.094)	(0.045)	(0.072)
LNESTIMATED	-0.119	-0.029	0.562^{**}	$0.167^{\dagger}$	0.424^{*}
	(0.211)	(0.182)	(0.174)	(0.094)	(0.174)
CV controls	Yes	Yes	Yes	Yes	Yes
N	93	67	59	82	75
R^2	0.638	0.830	0.902	0.922	0.782

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience. All regressions include employer fixed effects.

Table 16: The impact of beauty and confidence on wages in treatments (0) to (FTF) - employers of below average beauty only

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	0.665**	-0.293	-0.058	0.190	-0.130*
	(0.188)	(0.268)	(0.132)	(0.236)	(0.058)
AGE*AGE	-0.014**	0.006	0.000	-0.004	0.002†
	(0.004)	(0.006)	(0.003)	(0.005)	(0.001)
MALE	0.075	0.002	0.095	0.059	-0.031
	(0.087)	(0.110)	(0.070)	(0.107)	(0.125)
UNIV2	0.291	0.152	0.211*	0.074	-0.199
	(0.174)	(0.154)	(0.086)	(0.183)	(0.149)
UNIV3	-0.082	0.218	-0.014	-0.084	0.032
	(0.192)	(0.304)	(0.145)	(0.211)	(0.258)
INTERNET	-0.148	-0.044	0.032	0.007	0.081
	(0.093)	(0.092)	(0.069)	(0.086)	(0.095)
TEAMSPORT	-0.069	-0.075	-0.072	0.063	0.003
	(0.084)	(0.101)	(0.065)	(0.088)	(0.111)
PREDICT	0.455**	0.380**	0.314**	0.224**	0.326**
	(0.071)	(0.082)	(0.050)	(0.074)	(0.074)
LNACTUAL	-0.068	-0.080	-0.184**	-0.014	0.089
	(0.088)	(0.110)	(0.067)	(0.106)	(0.086)
BEAUTY	0.018	0.027	0.086*	0.075	0.114
	(0.047)	(0.072)	(0.038)	(0.078)	(0.070)
LNESTIMATED	0.154	0.320†	0.202**	0.257*	0.085
	(0.110)	(0.162)	(0.075)	(0.118)	(0.164)
CV controls	Yes	Yes	Yes	Yes	Yes
N	70	94	104	80	88
R^2	0.85	0.689	0.839	0.806	0.727

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience. All regressions include employer fixed effects.

Table 17: Test of persuasion channel in treatments (0) to (FTF)

Variable	(0)	(P)	(T)	(PT)	(FTF)
AGE	0.001	-0.010	-0.029	0.075†	-0.136**
	(0.047)	(0.042)	(0.036)	(0.039)	(0.045)
AGE*AGE	0.000	0.000	0.000	-0.001*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.065	0.062	0.127*	0.185**	0.082
	(0.070)	(0.065)	(0.053)	(0.057)	(0.068)
UNIV2	0.124	0.101	0.089	-0.074	0.021
	(0.107)	(0.094)	(0.080)	(0.086)	(0.103)
UNIV3	0.308*	0.161	-0.095	-0.304*	0.101
	(0.152)	(0.141)	(0.118)	(0.126)	(0.152)
INTERNET	0.035	-0.020	0.050	-0.014	0.048
	(0.065)	(0.059)	(0.050)	(0.054)	(0.063)
TEAMSPORT	0.000	-0.025	-0.049	-0.023	-0.068
	(0.067)	(0.059)	(0.051)	(0.054)	(0.064)
PREDICT	0.419**	0.380**	0.324**	0.297**	0.296**
	(0.052)	(0.046)	(0.040)	(0.044)	(0.050)
LNACTUAL	-0.033	0.002	-0.052	0.053	-0.046
	(0.064)	(0.059)	(0.050)	(0.056)	(0.062)
BEAUTY	-0.175	0.271*	0.017	0.139	0.164
	(0.110)	(0.109)	(0.088)	(0.090)	(0.106)
LNESTIMATED	-0.016	0.105	0.206**	0.183**	0.335**
	(0.097)	(0.093)	(0.065)	(0.069)	(0.097)
LNESTIMATED*BEAUTY	0.102†	-0.082†	0.036	-0.021	-0.023
	(0.054)	(0.049)	(0.042)	(0.045)	(0.052)
CV controls	Yes	Yes	Yes	Yes	Yes
N	163	161	163	162	163
R^2	0.618	0.702	0.782	0.791	0.647

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience. All regressions also include interaction terms between SETWAGE and BEAUTY and LNESTIMATED to control for direct discrimination. All regressions include employer fixed effects.

Table 18: Estimation of unified model

Variable	**Coefficient**	**(Std. Err.)**
AGE	-0.015	(0.019)
AGE*AGE	0.000	(0.000)
MALE	0.100**	(0.029)
UNIV2	0.069	(0.042)
UNIV3	0.040	(0.062)
INTERNET	0.027	(0.026)
TEAMSPORT	-0.030	(0.027)
PREDICT	0.400**	(0.043)
PREDICT*VISUAL	0.011	(0.060)
PREDICT*AUDIO	-0.122*	(0.060)
PREDICT*VISUAL*AUDIO	0.054	(0.084)
PREDICT*FTF	-0.066	(0.060)
LNACTUAL	-0.013	(0.026)
BEAUTY	-0.007	(0.026)
BEAUTY*VISUAL	0.072*	(0.035)
BEAUTY*AUDIO	0.104**	(0.035)
BEAUTY*VISUAL*AUDIO	-0.094†	(0.050)
BEAUTY*FTF	0.052	(0.035)
LNESTIMATED	-0.038	(0.060)
LNESTIMATED*VISUAL	0.043	(0.083)
LNESTIMATED*AUDIO	0.292**	(0.083)
LNESTIMATED*VISUAL*AUDIO	-0.060	(0.117)
LNESTIMATED*FTF	-0.125	(0.083)
N	812	
R^2	0.619	
$F_{(204,607)}$	24.666	

Significance levels : † : 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. The base university is UNT. The CV controls include participation in team sports, choice of college major, hobby variables and previous job experience.